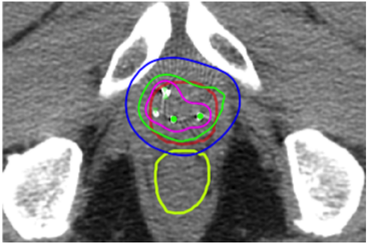
Deep generative model-driven multimodal prostate segmentation in radiotherapy

Kibrom B. Girum, Gilles Créhange, Raabid Hussain, Paul M. Walker, Alain Lalande

MICCAI-2019: Artificial Intelligence in Radiation Therapy

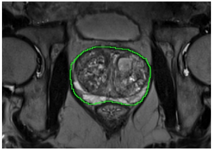
Prostate brachytherapy

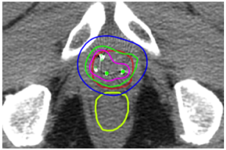
- Planning
- Intra-operative procedures
- Post-procedural dose analysis



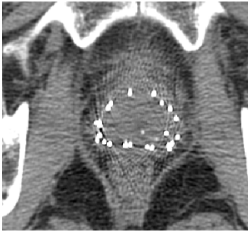
Prostate segmentation in brachytherapy

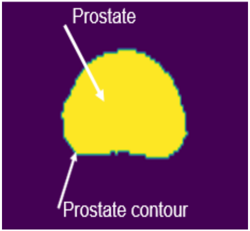
- **Magnetic resonance images (MRI):**
  - ✓ Relatively better contrast for the contour of the prostate and rectum
  - x Difficulties in relating the tissue density with the voxel intensity value
  - x Low signal for the radioactive seeds
- **Computed tomography images (CT):**
  - ✓ Relate the tissue density with the voxel intensity value
  - ✓ Good signal for radioactive seeds
  - x Low-contrast for the contour of the prostate





Related works

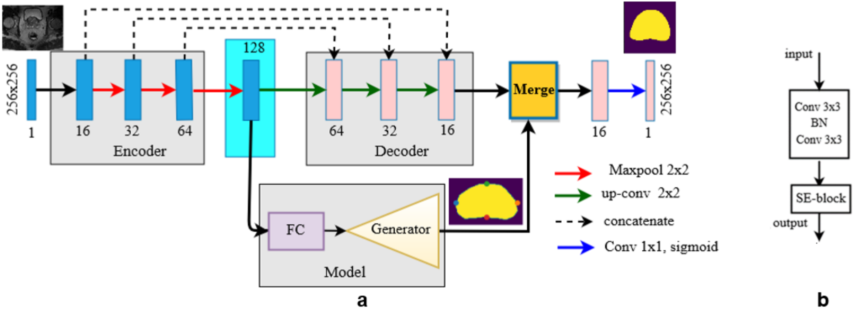




- Pixel classification with U-net[1]
- Combination of information from contour and/or shape with pixel classification[2]
- Combination of convolutional neural network (CNN) based pixel classification with atlas of the prostate gland[3]

[1] Kazemifar S. et al. 2018, Biomed Phys Eng Express
[2] Martínez F. et al. 2014, Phys. Med. Biol.
[3] Ma L. et al. 2017, SPIE

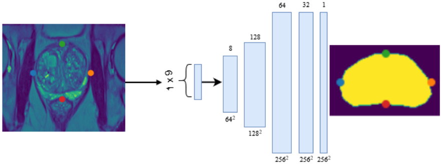
Proposed architecture



Proposed architecture: (a) The overall framework (DGMNet), and (b) The schema of a single block in the encoder and decoder

Proposed architecture

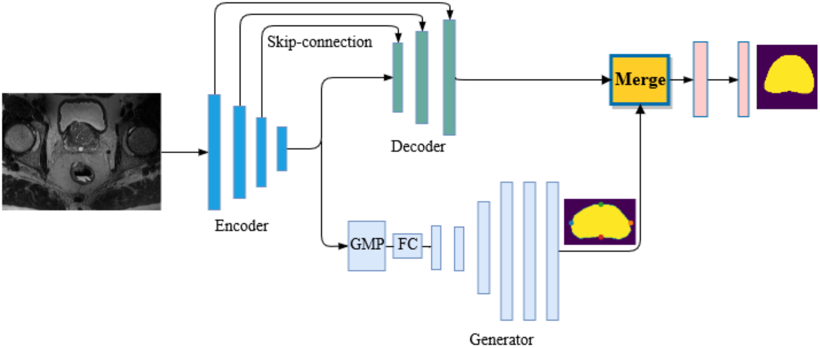
- Regression for surface coordinates x and y
- Image based classification z



Generator

- Binary cross entropy loss

Proposed architecture



The number of feature channels in the Encoder/Decoder is 16 in the first level, which is then doubled/halved after each pooling/upsampled with a maximum of 128 features channels at the bottleneck.

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Cost function

$$L_{total} = L_{mask} + \lambda L_{clsLnd} \ , \qquad (1)$$

where the segmentation loss is: $L_{mask} = L_{dice} + L_{CE}$

Given $I^u = (x^u, y^u, z^u)$, and $I^v = (x^v, y^v, z^v = p)$, the joint classification and regression loss can be calculated as:

$$L_{clsLnd}(I^u, I^v) = L_{cls}(p, z^u) + [z^u = 1] L_{lnd}(t^u, t^v) \ , \qquad (2)$$

$$L_{lnd}(t^u, t^v) = \sum_{i \in \{x,y,z=1\}} smooth_{L1}(t_i^u - t_i^v) \ , \qquad (3)$$

in which

$$smooth_{L1}(\Delta t) = \begin{cases} 0.5(\Delta t)^2 & \text{if } |\Delta t| < 1 \\ |\Delta t| - 0.5 & \text{otherwise} \ , \end{cases} \qquad (4)$$

Dataset

- T2-weighted magnetic resonance images (MRI)
  - 60 T2-weighted MR exams
  - In-plane resolution ranging from 0.312 x $0.312\ mm^2$ to 0.676 x $0.676\ mm^2$
  - Slice thickness between $1.250\ mm$ and $2.722\ mm$
- Computed tomography (CT) images
  - 40 CT exams
  - Permanent prostate brachytherapy with ^{125}I
  - In-plane resolution ranging from 0.4 x $0.4\ mm^2$ to 0.58 x $0.58\ mm^2$
  - Slice thickness between $1.5\ mm$ and $2.5\ mm$

Pre-processing

- Resolution of 0.5 x 0.5 x $1.25\ mm^3$ and 0.7 x 0.7 x $1.25\ mm^3$ for CT and MRI, respectively
- Resized and cropped to 256 x 256
- Zero-centered the intensity values and normalize by standard deviation

Training and testing

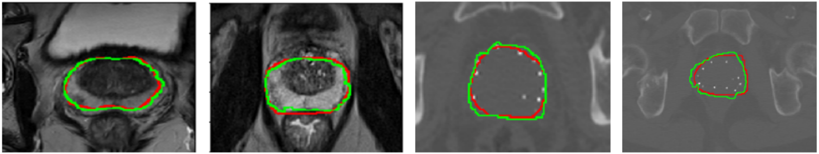
- 25% of the dataset were used for validation
- Experiments were performed using different metrics to investigate the effect of each layer in the proposed method

Quantitative results

Data	Method	DSC	Sen	ASD	PPV
CT	Unet	0.83 ± 0.04	0.76 ± 0.0.08	**0.16 ± 0.08**	**0.93 ± 0.03**
	ResUnet	0.82 ± 0.03	0.73 ± 0.03	0.16± 0.10	**0.93 ± 0.03**
	SE-ResUnet	0.84 ± 0.03	0.88 ± 0.05	0.84 ± 0.53	0.82 ± 0.06
	SE-Unet	0.85 ± 0.03	0.78 ± 0.07	0.17 ± 0.15	0.93 ± 0.04
	DGMNet	**0.89 ± 0.02**	**0.92 ± 0.03**	0.28 ± 0.09	0.87 ± 0.03
MRI	**DGMNet**	**0.93 ± 0.12**	**0.92 ± 0.15**	**0.11 ± 0.22**	**0.96 ± 0.07**

DSC: Dice Similarity Coefficient
Sen: Sensitivity
PPV: Positive Predicted Value
ASD: Average Surface distance (in mm)

Qualitative results



a b

Qualitative evaluation of prostate segmentation on 2D: (a) T2-weighted MRI, and (b) CT images with seeds from low-dose-rate brachytherapy. The ground truth labels are shown in red and segmentation results in green.

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Summary and remarks

Take home message

- We proposed a new method to segment the prostate in multimodal images using shape modeling and pixel classification
- Embedding prior organ knowledge via learning-based shape modeling and registration from better contrast images can improve segmentation on low-contrast images

Future work

- Evaluate on larger multi-center dataset
- Apply to intra-operative TRUS image segmentation
- Generalize the proposed method on other organs such as the heart and the lung

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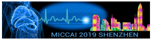

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